



9th Conference of the International Sports Engineering Association (ISEA)

Development of a Novel System for Monitoring Strength and Conditioning in Elite Athletes

D. Gordon^{*a}, S. L. Mullane^a, P. P. Conway^a, A. A. West^a

^a*Sports Technology Institute, Loughborough University, Loughborough, Leicestershire, LE113TU, United Kingdom*

Accepted 09 March 2012

Abstract

The aim of the research outlined in this paper was to determine the feasibility of using a network of wireless inertial measurement units (IMUs) to determine velocity-time and power-time relationships in weight training. Inertial navigation system (INS) algorithms have been implemented to account for rotation during a lift. A wireless IMU has been developed by Loughborough University that allows multiple IMUs to be networked using an adapted SimpliciTl protocol. An Olympic barbell has been modified to allow non-invasive attachment of an IMU whilst ensuring bar rotation is captured. Velocity (in the inertial frame) has been determined through integration of accelerometer / gyroscope data allowing calculation of true force and power. Three-dimensional force and 2.5 dimensional video data were simultaneously captured to provide validation for the IMU-determined force and power calculations.

© 2012 Published by Elsevier Ltd. Open access under [CC BY-NC-ND license](https://creativecommons.org/licenses/by-nc-nd/4.0/).

Keywords: Weight lifting; jump squat; force; accelerometer; power clean

1. Introduction

It is well accepted that resistance training has many benefits including an increase in muscular strength, power and endurance [1, 2]. Resistance training is a term broadly used to describe work performed against an external resistance, e.g. free weights or resistance machines. Whilst resistance machines are generally safer for an inexperienced user, it has been shown that training with free weights can better develop inter and intra-muscular co-ordination and can increase muscle activity [3, 4]. Parameters used in research to investigate performance in resistance training include peak force, rate of force development, peak velocity, peak power and acceleration [5-7]. Whilst these have been shown to be appropriate measures of performance, it has been suggested that analysis of the complete time series can

* Corresponding author. Tel.: +44-1509-564812.

E-mail address: d.gordon@lboro.ac.uk.

give further insight into specific changes in performance [8]. Power is important to athletes performing explosive exercises such as sprinting or rapid changes in direction [6]. There has been a significant amount of research investigating the relationship between force and velocity and, in particular, investigating the load at which maximum power can be generated [6, 8]. Acceleration has been used to indicate fatigue [9] and to measure force and power [10].

Force platforms have been used to determine vertical jump height [11] and performance characteristics in various weight lifting exercises [6-8, 10]. These methods determine parameters with respect to the system centre of mass, however they are unable to distinguish between the movement of the bar and the movement of the athlete [7]. Linear Position Transducers (LPTs) have been used to determine power output of the bar [7]. This method does not consider movement of the subject with respect to the bar and therefore may neglect key parameters in the lift. Furthermore, a single LPT is unable to distinguish between horizontal and vertical displacement, introducing more uncertainties. It has been shown that using two LPTs can account for horizontal trajectory therefore reducing this uncertainty [7]. Due to their respective limitations, it has been speculated that a combination of kinetic and kinematic data collection may be the most appropriate means of determining power output [7]. Accelerometers have been shown to provide a valid estimate of power output [10, 12]. Crewther et al. [10] have shown that peak force and peak power determined from the commercially available MYOTest were moderately to strongly correlated ($P \leq 0.05$ - 0.001 , $r = 0.66$ - 0.97) with values determined from a force platform for a squat. Thomson and Bembien [12] have shown average power determined from a single axis accelerometer to be significantly correlated ($r = 0.95$) to average power determined from video data for a bench press. In this study the exercise was performed on a Smith machine, which restricts motion to a single plane. Errors can be introduced into the system if there is significant rotation of the sensor throughout the exercise, as the accelerometer is only capable of measuring movement with respect to its local axes [13]. This can be overcome if the orientation of the sensor is known throughout the range of motion, which can be measured using a gyroscope. Accelerometers and gyroscopes used in combination to measure 3-axes of movement are known as inertial measurement units (IMU) [13]. Algorithms used to project the local accelerations onto a global frame are known as Inertial Navigation Systems (INS). The use of an INS to quantify sporting performance has been explored in other domains, such as skiing [14]; however, the use of an INS in weight lifting is an area that has not yet been explored. Research presented in this paper aims to investigate the feasibility of using a wireless sensor node (WSN), developed at Loughborough University, to determine velocity-time and power-time curves during weight-lifting. The WSN measures acceleration and angular velocity in three orthogonal axes and transmits wirelessly to an access point that is connected to a personal computer. Several WSNs are networked using a star topology, which allows multiple athletes or multiple segments to be monitored synchronously.

2. Methodology

An elite male basketball player with more than 2 years experience of weight training was asked to perform a total of 12 repetitions (reps) consisting of; 3 sets of 1 rep of an un-weighted Countermovement Jump (CMJ) and 3 sets of 1 rep of a Hang Power Clean (HPC) at 40Kg, 50Kg and 60Kg. The athlete was required to perform each rep whilst stood on two force platforms, i.e. one under each foot. The athlete was asked to remain still for 1s at the start and end of each rep to ensure boundary conditions were kept the same. The experimental set-up used for preliminary testing is shown in Fig. 1.

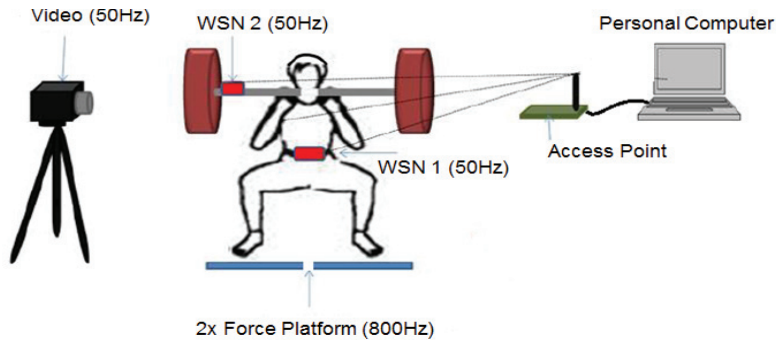


Fig. 1. Experimental set-up; Athlete performed exercises whilst standing on two Kistler 9281CA force platforms recording at 800Hz. Video data was captured at 50 Hz in sagittal plane. WSN was attached to the waist and transmitted wirelessly to a remote access point, which was connected to a PC

2.1. Data Collection

Two Kistler force plates (type 9281CA) [15] were used to record ground reaction force in 3 axes at 800Hz sampling rate. Video data recorded 2D movement in the sagittal plane using a Photron Fastcam SA1 high-speed camera [16] sampling at 50Hz. A WSN was attached to the athlete's torso to provide an approximation of the movement of centre of mass. The WSN collected data at 50Hz and transmitted wirelessly to a PC via an access point.

2.2. Data Manipulation

Force Plate (FP) data were manipulated using the impulse-momentum relationship (1) and (2) to obtain velocity. Power was then calculated by multiplying the velocity and the force using the system mass.

$$F = VGRF - (m_{athlete} + m_{lifted}) * g \quad (1)$$

$$F(t) = (m_{athlete} + m_{lifted})(v_1 - v_2) \quad (2)$$

Video data were initially processed using Image Pro Plus V6.2 to track manually the position of the WSN on the torso (VT) and the position of the bar (VB). An algorithm, developed in Matlab R2011a, was then used to differentiate position to obtain velocity. A low pass Butterworth filter [17] was used to filter velocity before differentiating to obtain acceleration. The acceleration of the torso was multiplied by the system mass to obtain athlete force, whilst the acceleration of the bar was multiplied by the lifted mass to obtain bar force. Power was then calculated for each trace by multiplying force and velocity traces.

WSN data were post processed using modified INS algorithms in Matlab R2011a. During motion, three orthogonal gyroscopes were used to measure angular velocity, these were integrated to obtain the angle and hence orientation of the sensor at any given time. A time dependent error was introduced through cumulative integration of the angular velocity. To reduce this error, individual reps were analysed and it was assumed that the athlete and bar were stationary at the start and end of each rep. This allowed the WSN orientation to be determined from the accelerometer at the beginning and end of each rep. This information was used to provide a corrective factor for the integrated gyroscope trace to reduce error. Once the orientation at each point was known the local acceleration of the sensor was filtered using a low pass Butterworth filter (5th order, cut off frequency 8Hz). Local accelerations were projected on to a set of global co-ordinates by multiplying through a transformation matrix. Global velocities were calculated by

integrating the global acceleration with respect to time. Sensor velocity was assumed to be zero at the start and end of each rep, allowing a corrective factor to be applied to the velocity. The global acceleration of the WSN was multiplied by the system mass to obtain force. Power was calculated by multiplying force and velocity traces.

3. Results

Error in Peak Velocity (PV), Time to Peak Velocity (TPV), Peak Power (PP), Time to Peak Power (TPP) and the Force at peak Power (PF) for both exercises are reported in Table 1. Video data of the torso (VT) were used as an absolute reference for WSN data, since it measured the movement of the sensor. The WSN showed a good estimate for PV in the Hang Power Clean (HPC) with a 2.8% error ($\pm 2.71\%$), whilst PF showed a 9.5% error ($\pm 6.3\%$). It was expected that PF would be more accurate than PV, since the force is the acceleration multiplied by a constant value and acceleration is directly measured by the WSN. This error may be due to uncertainty in the VT, since these data have been differentiated and filtered twice. Interestingly, the estimate for PV and PF was shown to be less accurate for a CMJ. This is not as expected as the CMJ is a less complex exercise than HPC. Contrary to this, the estimate for PP was shown to be more accurate for CMJ than HPC. TPV exhibited the least error in both exercises, whilst error in TPP was also seen to be very low (2.6%-0.09%). This suggests that the WSN exhibits a similar trace to VT but is not as accurate at peak values. To further investigate this, analysis of the error over the entire time series has been carried out. Fig. 2 (a) is a histogram plot of the error of the WSN velocity (VT-WSN), and Fig. 2 (b) is a histogram plot of the error of the WSN power (VT-WSN). These plots reveal that the errors in velocity follow a normal distribution centred on -0.0129 m/s whilst errors in power follow a normal distribution centred on -21.5 W .

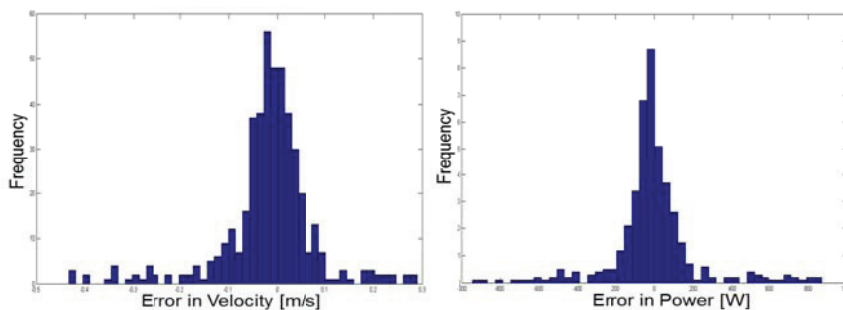


Fig. 2. Histogram of (a) Error in velocity for Hang Power Clean; (b) Error in Power for Hang Power Clean

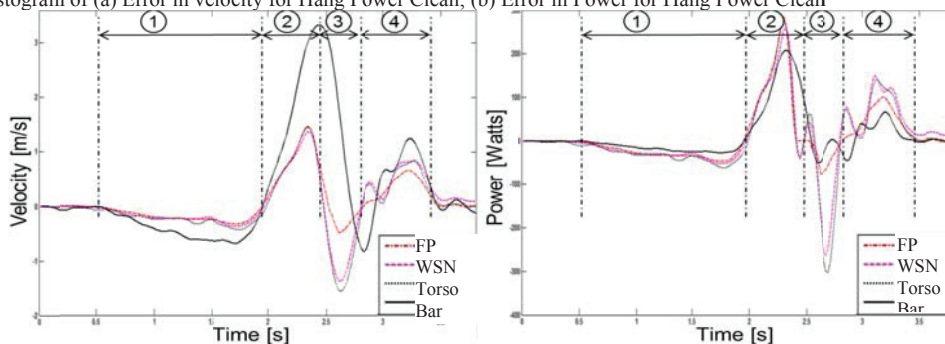


Fig. 3. Showing traces for Force Platform (FP), WSN, video trace of the Torso and video trace of the Bar for (a) Velocity vs. Time for a Hang Power Clean; (b) Power vs. Time for a Hang Power Clean. Highlighted are phases (1). Lowering of bar, (2). 1st and 2nd pull, (3). Catch, (4). Final leg extension

Table 1. Mean error for HPC and CMJ

Exercise	Measured Variable	VT - WSN		VT - FP		WSN - FP	
		Mean Error (%)	Std Dev	Mean Error (%)	Std Dev	Mean Error (%)	Std Dev
HPC	PV	2.8	2.71	5.1	4.3	7.5	1.3
	PF	9.5	6.3	2.1	1.64	9.0	3.5
	PP	14.1	7.2	3.9	1.7	15.8	6.4
	TPV	0.28	0.49	0.05	0.053	0.26	0.42
	TPP	0.53	0.47	0.09	0.04	0.53	0.42
CMJ	PV	6.1	2.17	28.8	6.2	23.46	6.97
	PF	12.5	3.4	41.2	6.9	32.7	7.4
	PP	12.5	3.4	24.9	2.638	12.4	1.625
	TPV	0.034	0.058	0	0	0.034	0.058
	TPP	1.01	0.90	1.70	0.48	2.58	1.44

To gain a better understanding of where the errors occurred, the complete velocity and power time series have been investigated (Fig. 3 (a) and Fig. 3 (b)). The main phases of the HPC are highlighted as;

1. Lowering of the bar
2. 1st and 2nd pull
3. Catch
4. Final leg extension

From Fig. 3 (a) it can be seen that the VT, FP and WSN traces followed a very similar path during phase 1 and 2. The WSN trace was 0.097m/s (6.6%) lower than the video trace at peak velocity, however force plate and video derived velocities show little difference (0.11%) at this peak. Velocity from video data of the bar (VB) was significantly higher (128%) and occurred 0.1s later. During phase 3 and 4 the FP trace differed significantly from the VT, VB and WSN. It can be seen that when the FP, VT and WSN velocities reach a minimum, the VB is positive. This opposing movement may explain the difference between the VT/WSN and FP velocities, since the FP measured the velocity of the centre of mass whilst the WSN measured the velocity of the torso. This highlights a need to measure the velocity of the bar and potentially other segments, such as the shank and thigh, to more accurately determine the entire time series of the system. However, since this deviation occurred after peak velocity, one WSN on the torso seems sufficient to predict peak velocity, force and power. The same trend can be seen in Fig. 3 (b), as FP, VT and WSN traces follow a similar path until phase 3 and 4. Power from VB follows the other three traces more closely than seen in the velocity trace. This is because the force from VB is the acceleration multiplied by the lifted mass (40Kg), rather than the system mass (100Kg+40Kg), resulting in a lower force.

4. Conclusion

The aim of this investigation was to explore the feasibility of using a wireless IMU to determine performance characteristics in weight lifting. A wireless sensor node (WSN) utilising three orthogonal accelerometers and gyroscopes has been used to estimate Peak Velocity, Peak Power and Peak Force for hang power clean and countermovement jump exercises. HPC and CMJ were chosen as they represent common resistance training exercises with different degrees of complexity. The results show that the WSN can be used to estimate PV, TPV and TPP with relatively good accuracy ($\pm 6\%$). High standard deviation in error in PF (3.4%-6.3%) and PP (3.4%-7.2%) gives less confidence in these variables. Error in acceleration may be due in part to manual video processing; at peak velocities the video was blurred leading to a 'best guess' marker. It is thought that increasing the frame rate will significantly reduce this error. Future work will be concerned with developing an integrated system using both the Force Platform and a network of WSNs to enable long term monitoring of athletes.

References

- [1] Rutherford O.M and Jones D.A, The role of learning and coordination in strength training. *Eur.J.Appl. Physio.* 55:100-105, 1986.
- [2] Adams K.J, O'Shea K.L, and Climstein M, The effect of six weeks of squat, plyometric and squat-plyometric training on power production, *J Appl. Sport Sci. Res.* 6:36-41, 1992.
- [3] ACSM, Progression models in resistance training for healthy adults, *Med Sci Sports Exe*, 2002.
- [4] Mccaw & Friday, A comparison of muscle activity between a free weight and machine bench, 1994.
- [5] Stone, Michael H. et al, Maximum Strength-Power-Performance Relationships in Collegiate Throwers, 2003, *Journal of Strength and Conditioning Research*, pp. 739-745.
- [6] Sleivert, Gord., Challenges in Understanding the Influence of Maximal Power Training on Improving Athletic Performance. s.l. : Sports Medicine, 2005, Vol. 35, pp. 213-234.
- [7] Cormie, P, McBride, J M, McCaulley, G O., Validation of Power Measurement Techniques in Dynamic Lower Body Resistance Exercises. 2007, *Journal of Applied Biomechanics*, pp. 103-118.
- [8] Cormie, P, McBride, J M, McCaulley, G O., Power-time, force-time, and velocity-time curve analysis of the countermovement jump: impact of training. s.l. : *Journal of Strength and Conditioning Research*, 2009, pp. 177-186.
- [9] Sato, K, Fleschler, P, Sands, B., A New Approach to Measure Weightlifting Performance: Introducing an Accelerometer.
- [10] Crewther, B T, Kilduff, L P, Cunningham, D. J, Cook, C., Owen, N., Yang, G. Z., Validating Two Systems for Estimating Force and Power. 2011, *Int Journal Sports Medecine*, pp. 254-258.
- [11] Walsh, M. S., Ford, K.R., Bangen, K. J., Myer, G.D., Hewett, T.E., The Validation of a Portable Force Plate for Measuring Force-Time Data During Jumping and Landing Tasks. s.l. : *Journal of Strength and Conditioning Research*, 2006, pp. 730-734.
- [12] Thompson, C. J., and Bemben, M. G, Reliability and comparability of the accelerometer as a measure of muscular power. *Medicine and Science in, Sports and Exercise*, 31, 897-902, 1999.
- [13] Woodman, Oliver J. An introduction to inertial navigation. s.l. : University of Cambridge, 2007.
- [14] Brodie, M., Walmsley, A., Wyatt, P., Fusion Motion Capture: The Biomechanics of Alpine Ski Racing., *Journal of Biomechanics.*, 2007.
- [15] Kistler Instruments Ltd, http://www.kistler.com/gb_en-gb/KistlerCountryHome_KIL/Kistler.html, Accessed on 29th Dec 2011
- [16] Photron, http://www.photron.com/index.php?cmd=product_general&product_id=4&product_name=FASTCAM+SA1.1, Accessed on 29th December 2011.
- [17] M.E. van Valkenburg, Introduction to Modern Network Synthesis, John Wiley & Sons, New York, 1960.